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Supplementary information

Dietary change in high-income nations alone can lead to substantial double climate dividend

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Dietary change in high-income nations alone can lead to substantial double climate dividend

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Supplementary Methods

Biomass carbon and soil organic carbon in current vegetation

The calculation of aboveground biomass carbon (AGBC) and belowground biomass carbon (BGBC) is based on the latest harmonized carbon density map in the year 2010 developed by Spawn et al[1]. For herbaceous crops, Spawn et al. employed gridded crop maps from EarthStat [2], and we used the latest crop maps from Spatial Production Allocation Model (SPAM) [3] in 2010 and method from Spawn et al. [1]to get the latest AGBC and BGBC maps of herbaceous crops. For woody crops and pasture, we extract AGBC and BGBC from the latest harmonized carbon density maps directly.

Primary crops and fodder:

The production and harvested area of 163 types of primary crops and 16 types of fodder crops in 2010 come from FAOSTAT [4]. The fodder crops are not available in FAOSTAT now, and are provided by one of developers of The Food and Agriculture Biomass Input-Output model (FABIO) [5]. We then use the SPAM [3] to build a spatially explicit picture of crop production. SPAM employs a cross-entropy approach to make estimates of 42 crop maps in 2010 at 5 arc min resolution. Since “Pearl Millet” and “Small Millet” are not split in FAOSTAT, we aggregate them into millet; similarly “Arabica Coffee” and “Robusta Coffee” are not split and we aggregate them into “Coffee”. These 40 crops are aggregated from an average of 163 types of primary crops contained in the FAOSTAT database between 2009 and 2011. Therefore, we used national data from FAOSTAT in 2010 to calibrate the SPAM for each country. However, since SPAM does not include fodder crop maps, we use EarthStat fodder maps [2] at 5 arc min resolution in 2000. We aggregate the 16 fodder maps into one fodder map for ease of analysis.

Pasture

There are many ways to estimate pasture for grazing. Ramankutty et al. created a map in which they estimate the percentage of pasture per grid cell at 5 min resolution [2] in 2000. Sloat et al., updated this map to the year 2010 at 500 meters resolution [6]. They considered a grid cell to be pasture if it fell into a livestock category on the global livestock production systems (GLPS) map and also contained at least 30% pasture by area [6]. Marques et al.,[7] used pasture map from Ramankutty et al.,[2] as permanent pasture, and excluded non-productive area (below NPP over 20 g C m^{-2} yr^{-1}) is used to feed livestock in the year 2000. In the end, we employed the pasture map developed by Sloat et al. [6] because their dataset is the latest and the time is in line with our research. We assume pasture layer was capped if all land-use types (cropland, infrastructure, and forest) fill 100% of the grid cell. For forest, we employed fractional tree cover from MODIS in 2010 [8]. We linearly stretched values such that 80% was treated as complete tree cover (100%), since MODIS tree cover estimates saturate at around 80%, following Spawn et al.[1]. For infrastructure, we used ESA CCI Land cover Maps at 300 meters resolution in 2010 [9].

GHG emissions

For animal-specific sectors, this includes: “Enteric Fermentation”, “Manure Management”, “Manure applied to Soils”, and “Manure left on Pasture”. For crop-specific sectors, this includes: “Rice Cultivation”, “Crop Residues”, and “Burning - Crop Residues”. There are two outstanding, high-emission sectors: “Synthetic Fertilizers”, and “Energy Use” which are not allocated to specific agricultural sectors. We updated the FAOSTAT estimates, using an older version of 100 year Global Warming Potentials (GWP), with those from the IPCC Fifth Assessment Report (AR5) with climate-carbon feedback (that is, 34 CO_2e for CH4 and 298 CO_2e for N_2O). In FAOSTAT, GHG emission of “Synthetic Fertilizers” is only derived from nitrogen fertilizers, so we first classify their GHG emissions into 28 countries/regions, and 13 crop groups based on the amount of nitrogen fertilizer use from the International Fertilizer Association (IFA) in 2010 [10]. Mapping relationship of countries and crops between FABIO and IFA see Tables S5 and S6. We then allocate GHG emission of "Synthetic Fertilizers" of 28 countries/regions, and 13 crop groups into separated countries and agricultural sectors in FABIO based on the monetary value of crops in each group from FAOSTAT [4]. Similarly, we allocate CO_2, CH_4, and N_2O from the "Energy Use" sector into 49 countries/regions and 14 agricultural sectors based on the combustion emissions of CO_2, CH_4, N_2O in EXIOBASE v3.6. Mapping relationship of countries and sectors between FABIO and EXIOBASE see Supplementary Tables S7 and S8. We then allocate these cases from "Energy Use" into agricultural sectors and countries using FABIO and based on the monetary value of crops from FAOSTAT in every group.

Dietary change in high-income countries

We used the difference between national food supply derived from FBSs and EAT-Lancet diet per person per day scaled by population as national food dietary change in the year 2010 (details see Method).

Physical input-output model for agricultural products: FABIO

FABIO describes the detailed input-output relationships between agricultural sectors within and between nations in the physical units. The input-output database traces biomass flows and embodied environmental pressures along global supply chains. For example, soybeans produced in Brazil, which are exported to feed cattle in China, which are then exported to South Korea for final consumption in the form of beef. However, FABIO does not cover non-agricultural sectors. Therefore, we did not investigate potential spillovers from the food sector into non-food sectors, such as the production of specific co-products of foods like leather.

Carbon change due to dietary shift

If increased crop or forage production is required and this exceeds spared agricultural land in that nation, we redirect some production from other nations. The redirection is attributed to other countries proportionally based on the original production of those other countries. This happens only in rare cases for small countries with very small production volumes, such as Antigua and Barbuda, Bahamas, and Bahrain.

Sensitivity Analysis

To test the sensitivity of the results, we focused on AGBC, BGBC, and SOC as they likely drive the largest uncertainties. For instance, while national uncertainties of consumption-based carbon accounts vary between 2 and 16% based on current MRIO tables (i.e. Eora, EXIOBASE, WIOD, GTAP, and OECD ICIO) [11], the coefficients of variation for BGBC and SOC are above 50% (Spawn, et al., 2020; Sousa et al., 2020). Some studies revealed that the Leontief inverse (L) may have the largest impact on consumption-based accounting when comparing different current GMRIO tables (Eora, WIOD, GTAP, EXIOBASE) [12,13]. However, the final demand may offset the impact. As such, the major differences of consumption-based accounting based on different GMRIO tables result from environmental data rather than the IO structure (e.g. 95% of the net difference in the UK's consumption-based carbon emissions) [12,13]. Future FABIO data revisions could add uncertainty as part of the data package in the same way the global

MRIO table, Eora, already does [5,14]. For biomass carbon, we used the uncertainty dataset from Spawn et al. (2020). For SOC, the uncertainty is defined as the ratio between the inter-quantile range (90% prediction interval width) and the median by SoilGrid v2.0. Therefore, we used the above scale parameter between the latest SoilGrid v2.0 and Sanderman et al. (2017) to provide the 5% quantile and 95% quantile of SOC in the top 100 cm. We assumed the error was normally distributed around the mean, and calculate the standard deviation based on the 5% quantile and 95% quantile value. We assumed error estimates are normally distributed and used mean ± 1 standard error as the lower bound and upper bound of AGBC and BGBC, and used mean ± 1 standard deviation for SOC. We cut values off at zero if the standard error is larger than the mean in some grid cells for the lower bound. These uncertainties are then used in the model framework to assess overall uncertainties.

Supplementary Discussion

Potential opportunities for carbon sequestration.

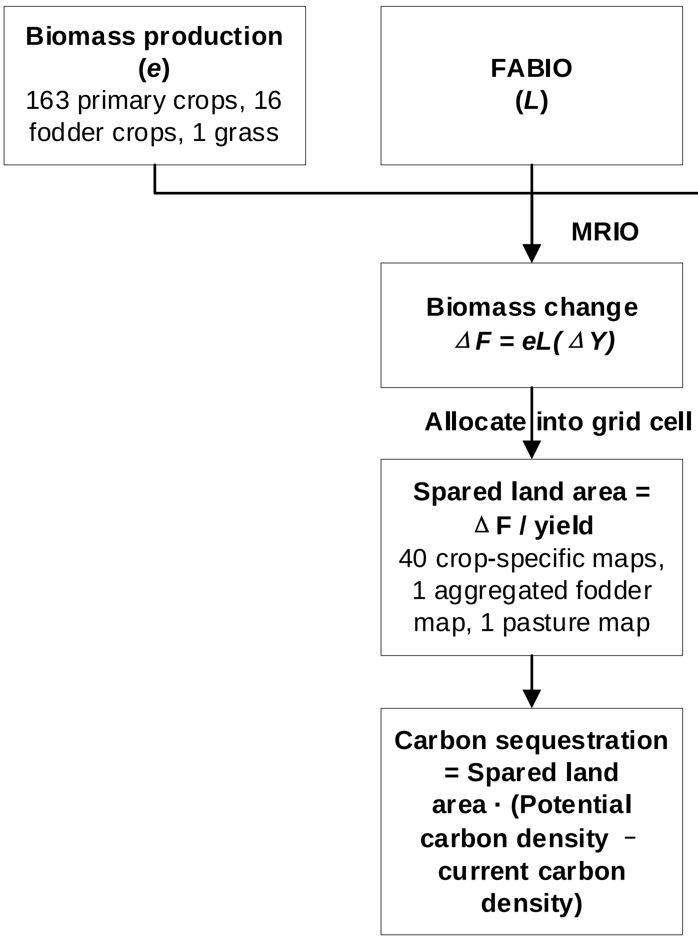
Climate-smart agriculture may provide another opportunity to increase carbon benefits [15]. For example, novel plants like intermediate wheatgrass (*Thinopyrum intermedium* (Host) Barkworth & D.R.Dewey) is an emerging cool-season perennial grain (the name for commercialized grain is “Kernza”) and forage dual-use grass, and its extensive root system can improve belowground carbon fixing and reduce soil erosion [16]. Intermediate wheatgrass is becoming commercially available to farmers for some areas in the US [17]. A further opportunity is biochar. While carbon stocks will saturate when the land restores to mature and stable vegetation, biochar can break the biophysical limits of carbon sequestration[18]. Feedstocks for biochar come from residues of forest/crop/pasture, animal manure, and food waste[18]. Removing forest residue can reduce risks of wildfire, but may disturb habitats of some fungi and wildlife, along with other ecosystem services [18]. This represents a tradeoff among carbon sequestration and other ecosystem services [18]. New technologies in agricultural production can also help to mitigate climate change. For example, 3-nitrooxypropanol (3NOP), a methane inhibitor, can persistently decrease enteric methane emissions by 30% under industry-relevant conditions without affecting animal productivity negatively [19], and has been approved as a feed additive in the European Union [20].

Potential carbon offset.

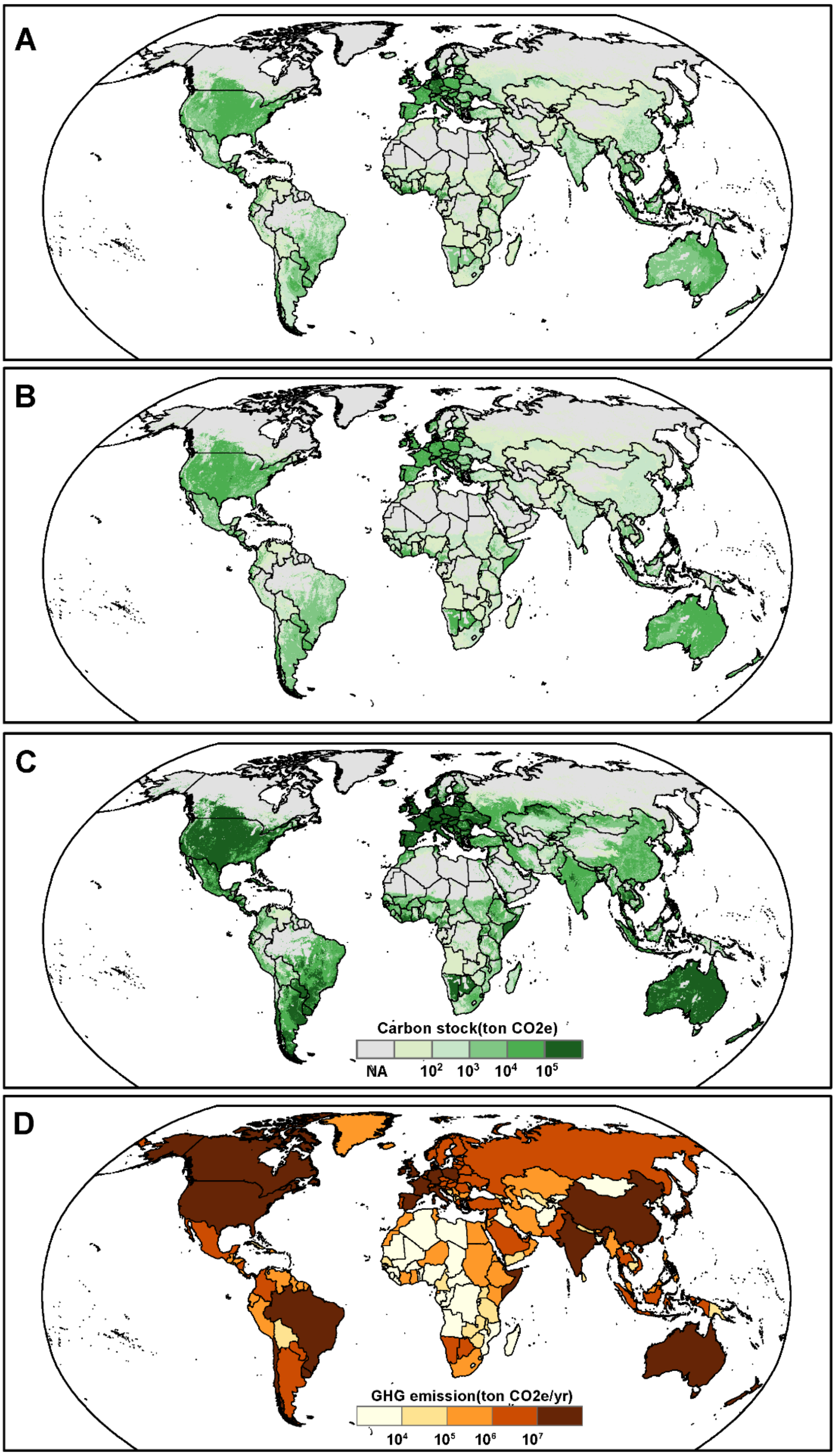
Here, we focus on dietary change in high-income countries where most food supply is higher than the recommendation in the EAT diet, and the dietary change could increase carbon sequestration and reduce CO2 emission. However, the carbon benefit may be offset by population growth and malnutrition in some low- and middle-income countries in the long term [21]. For example, most low- and middle-income countries face a severe double burden of malnutrition. That is, the simultaneous burden of undernutrition and overweight and obesity [22]. The obesity in low- and middle-income countries is due to overconsumption of cheap ultra-processed food and beverages resulting in an unhealthy diet [22]. The EAT diet is not always suitable in low-income countries because they cannot afford it, and it estimated at least 1.58 billion people are not able to pay for the cost of the EAT diet in the world [23]. People are likely to consume more food with income growth, especially animal products in low- and middle-income countries [24]. In addition, population growth in low- and middle-income countries will increase food needs further. For example, population is projected to increase by 199% (1 billion in 2017 to 3 billion by 2100) in Sub-Saharan Africa [25]. The increasing food demand in low- and middle-income countries could offset carbon benefit from dietary change in high-income countries.

Another carbon offset is food waste in high-income countries. EAT diet recommends per-capita food intake instead of food purchase. Pre-capita food waste is positively related to per-capita income, and most food waste occurs at the consumption stage in high-income countries because of overstocking, and too much cooking or serving [26]. In addition, healthier diets can cause more food waste because due to the increased consumption of perishable produce such as fruit and vegetables, which has substantial hidden costs via food waste [27]. It is estimated about one third of global food is lost or wasted [28]. If global food waste and loss were cut by 50% a further 0.9 Gt CO_2e yr^{-1} could be avoided [29].

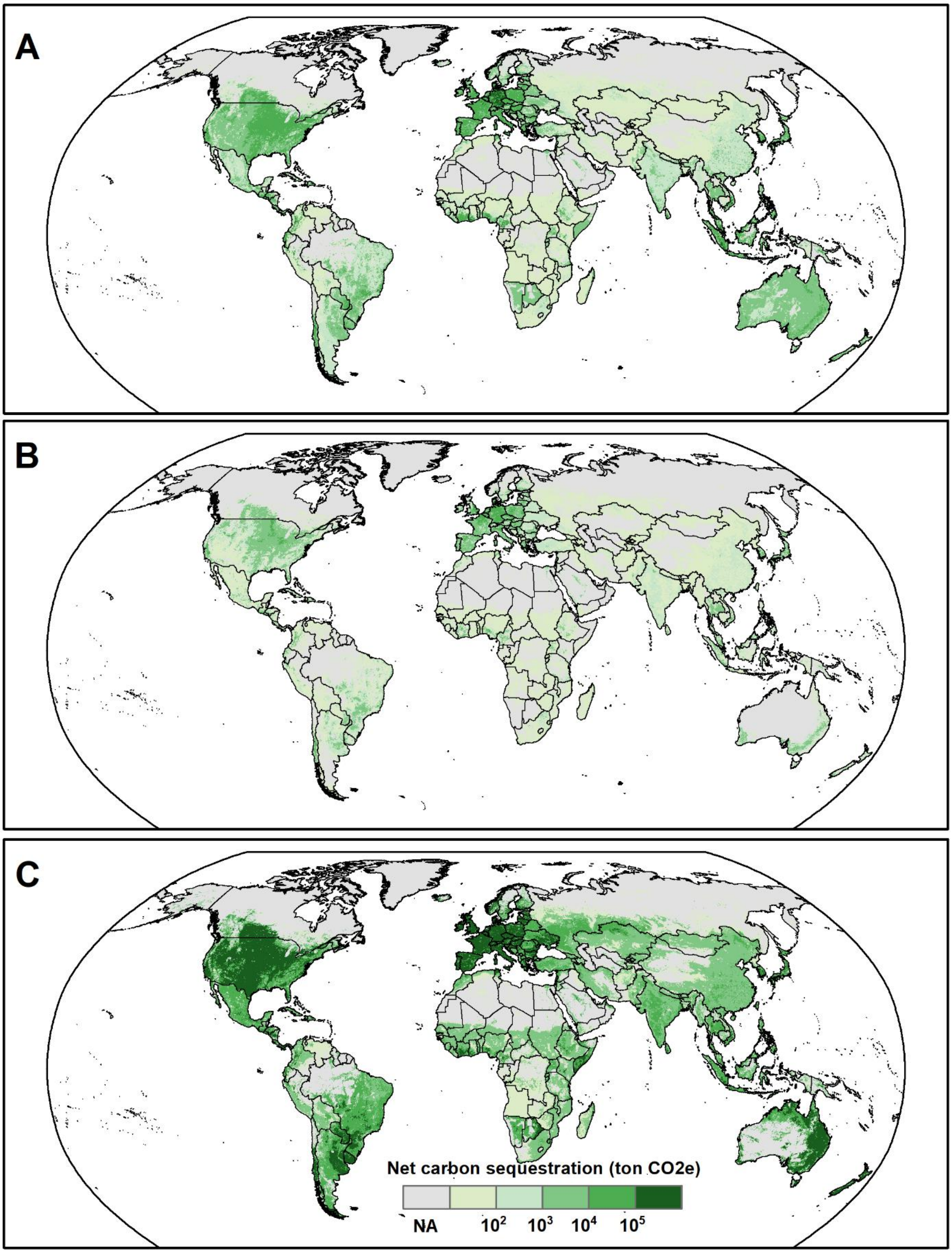
Recently, organic food consumption and organic agriculture production are surging in high-income countries due to shifts in food cultures and concerns over environmental impacts (e.g. less fertilizer or pesticide input, and fewer biodiversity losses). These food types often confer higher prices when compared to conventional farming [30,31]. Organic production has lower yield which means it needs more land use to satisfy the same food demand [30,31]. Higher quality and environmentally friendly food consumption can be at the expense of carbon benefits.



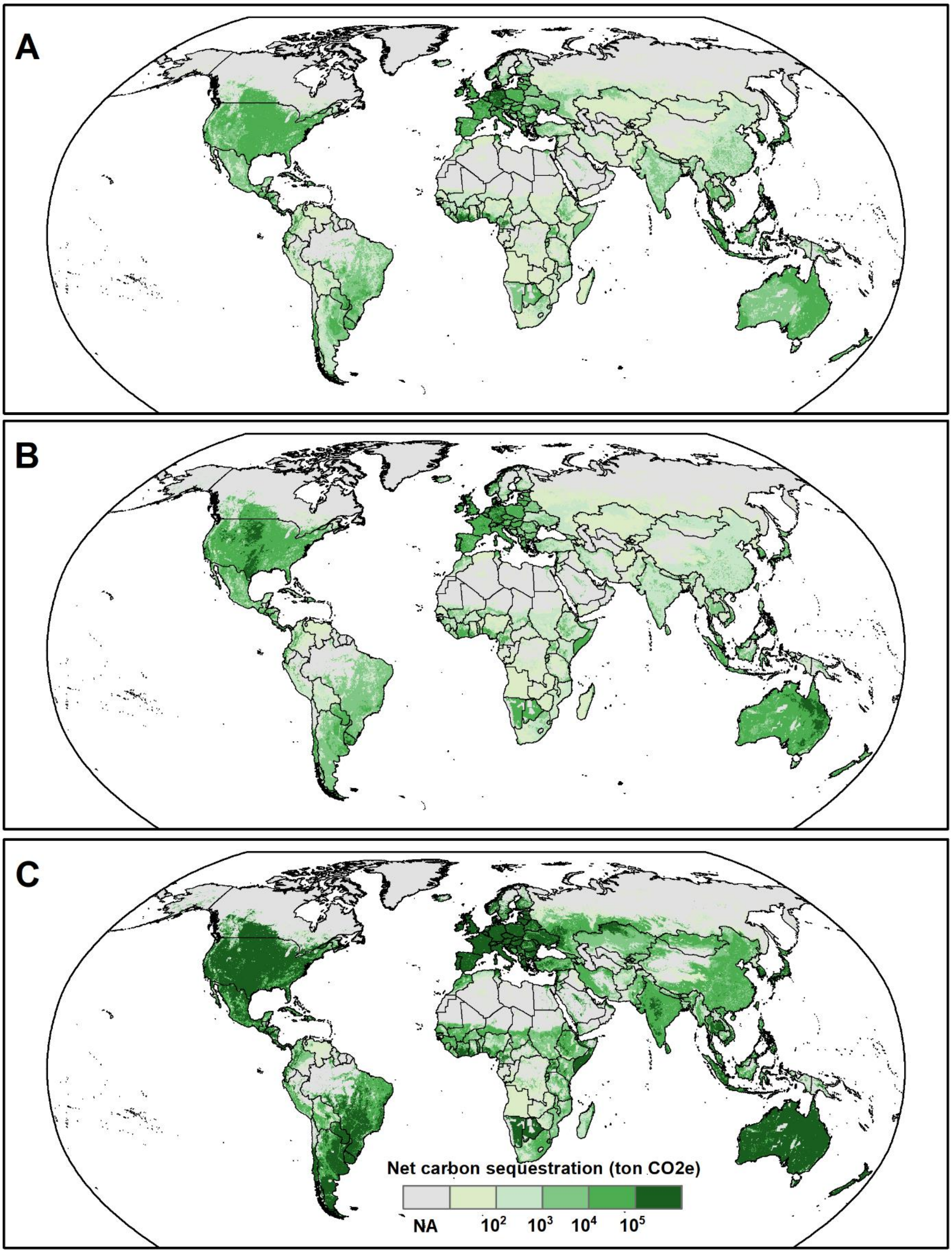
Supplementary Figure 1. A simplified visualization of the model framework for the calculation of carbon sequestration.



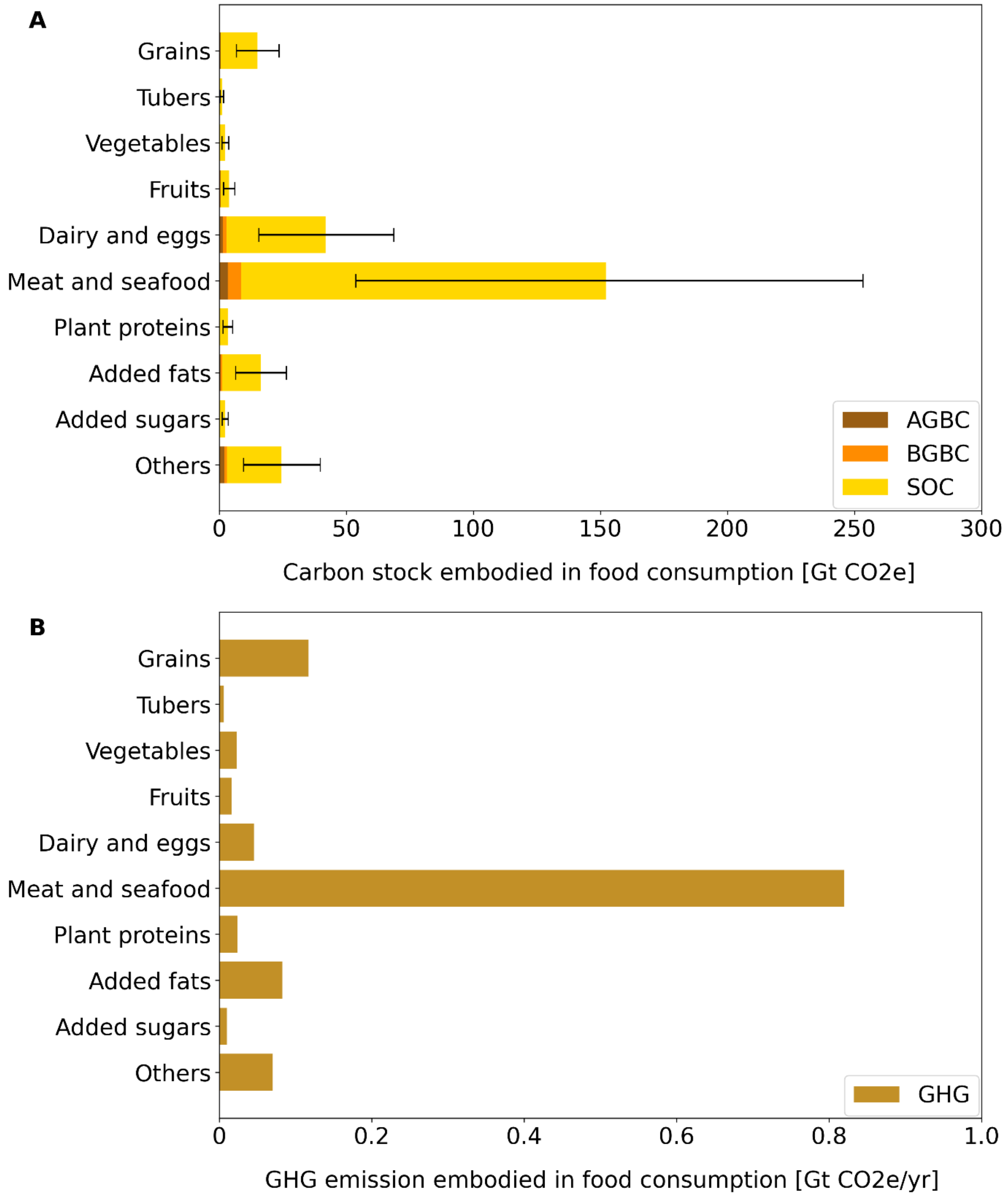
Supplementary Figure 2. Aboveground biomass carbon (AGBC, A), belowground biomass carbon (BGBC, B), soil organic carbon (SOC, C) and GHG emissions (D) embodied in current national average diets of high-income countries.



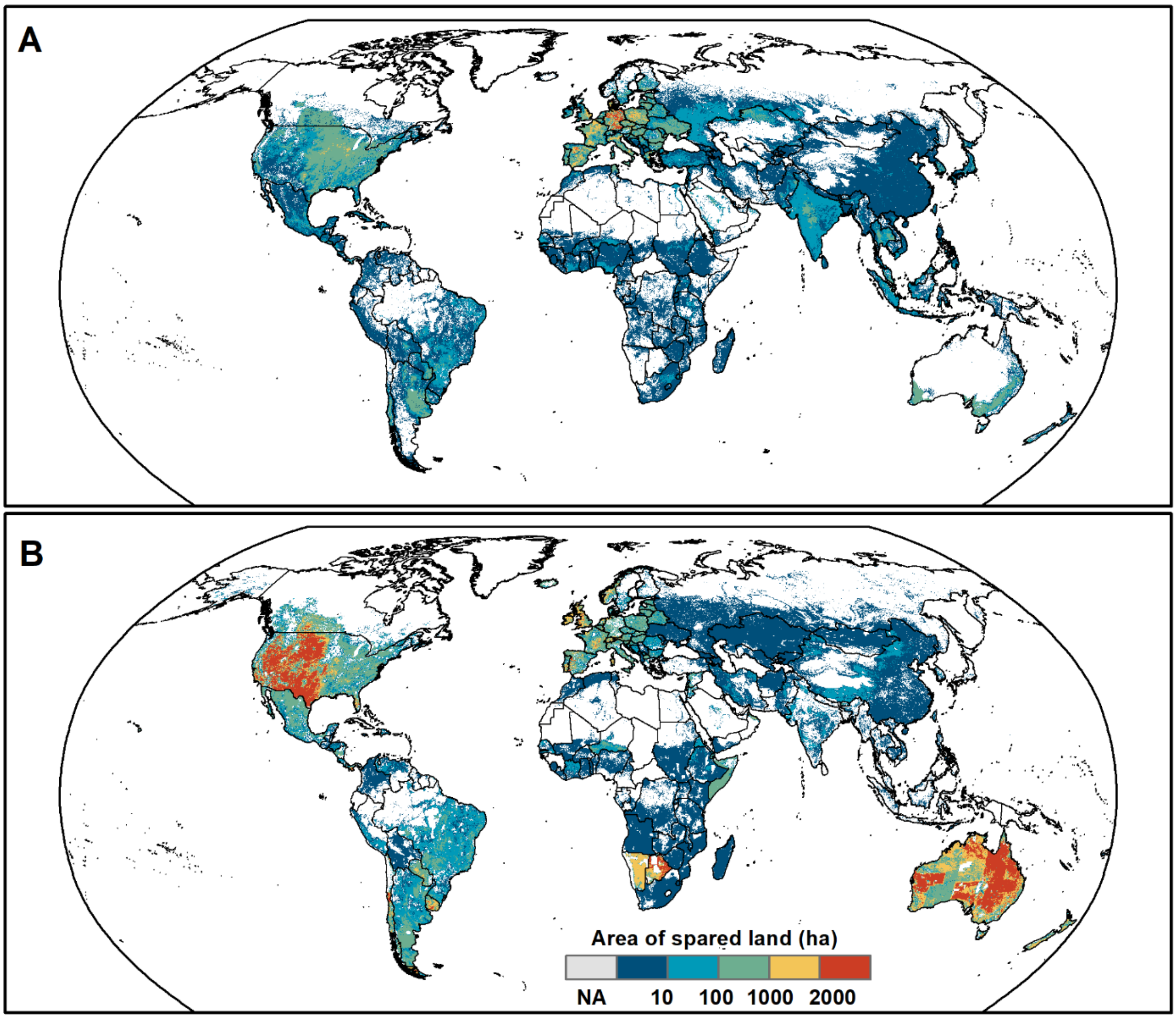
Supplementary Figure 3. Lower bound of aboveground biomass carbon (AGBC, A), belowground biomass carbon (BGBC, B), soil organic carbon (SOC, C) embodied in current national average diets of high-income countries.



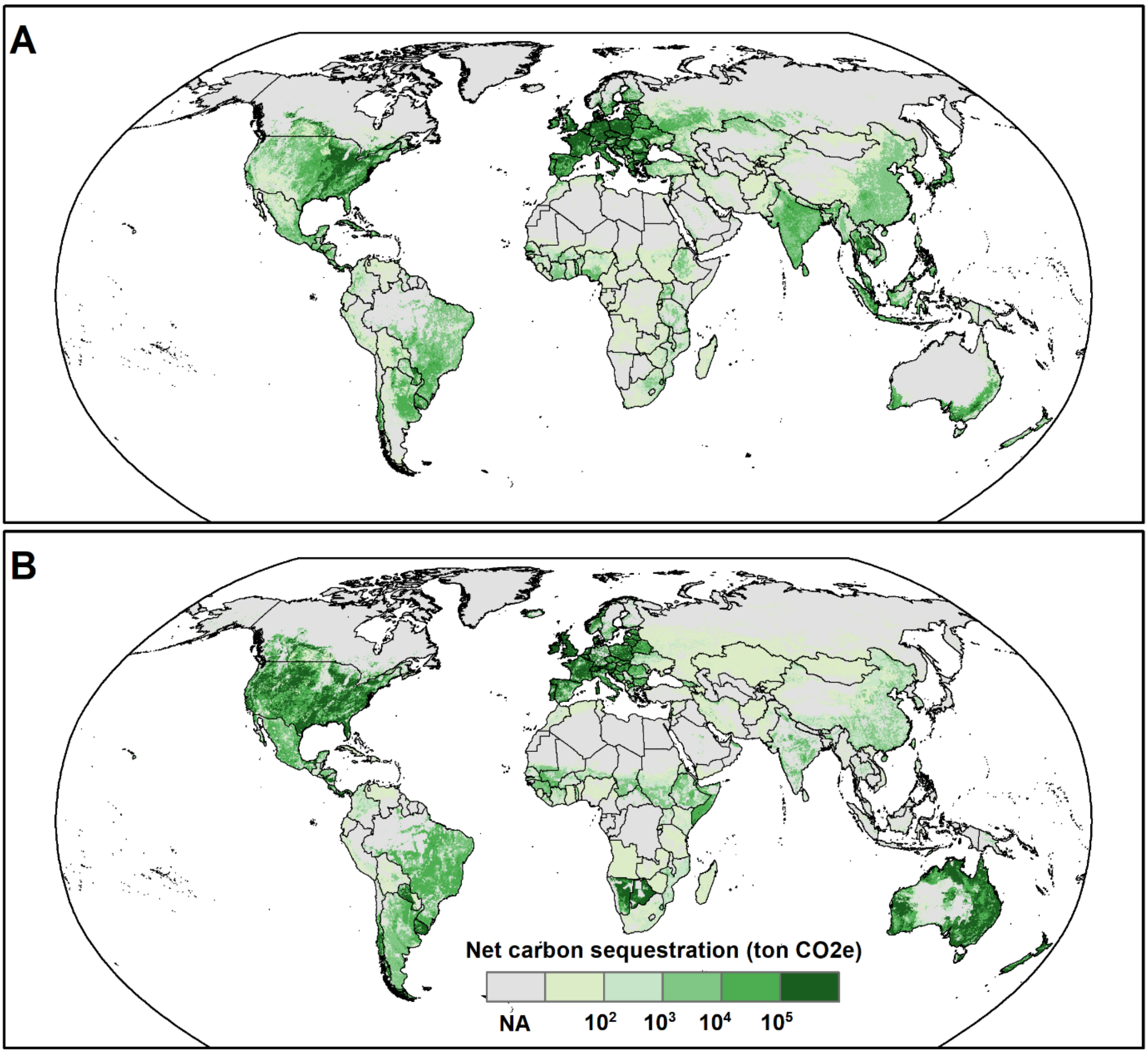
Supplementary Figure 4. Upper bound of aboveground biomass carbon (AGBC, A), belowground biomass carbon (BGBC, B), soil organic carbon (SOC, C) embodied in current national average diets of high-income countries.



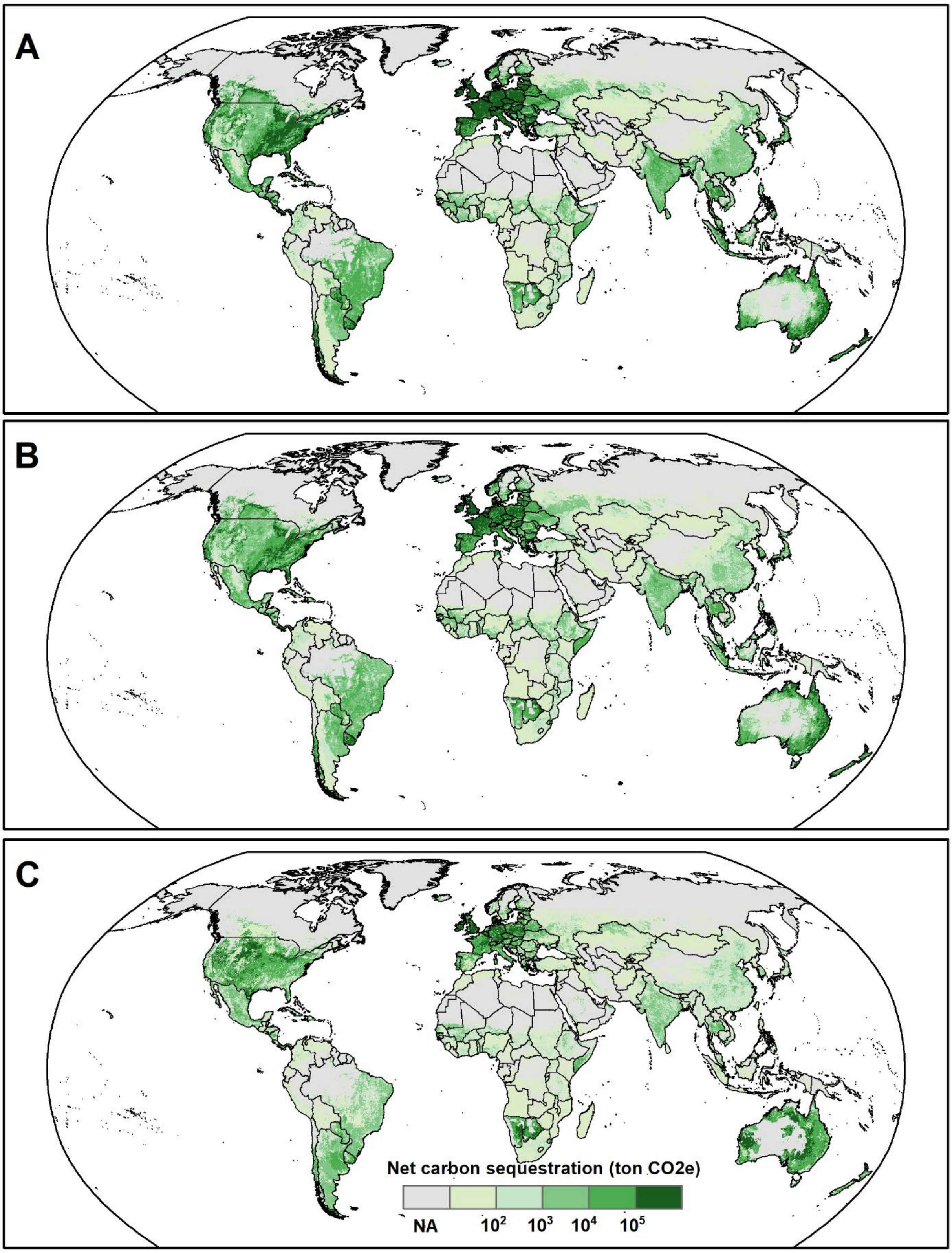
Supplementary Figure 5. Embodied carbon stocks (A) and GHG emission flows (B) in national average diets for high-income countries by food category. Carbon stock means aboveground biomass carbon (AGBC), belowground biomass carbon (BGBC), and soil organic carbon (SOC) in present agricultural production related vegetation (primary crops, fodder, and pasture) used for human food consumption.



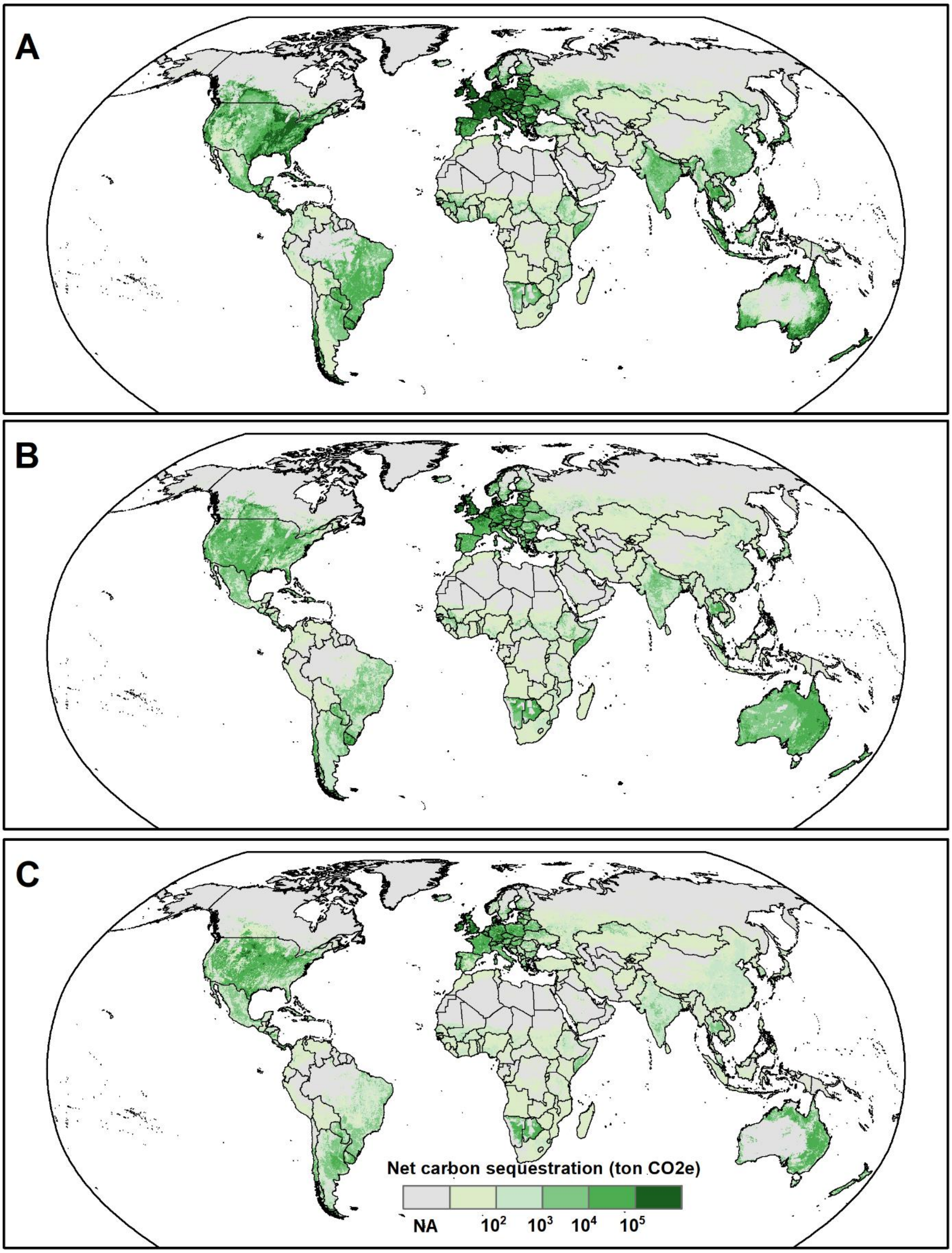
Supplementary Figure 6. Area of spared land due to dietary shifts from national average diets to EAT diet in high-income countries for cropland (A) and pastureland (B).



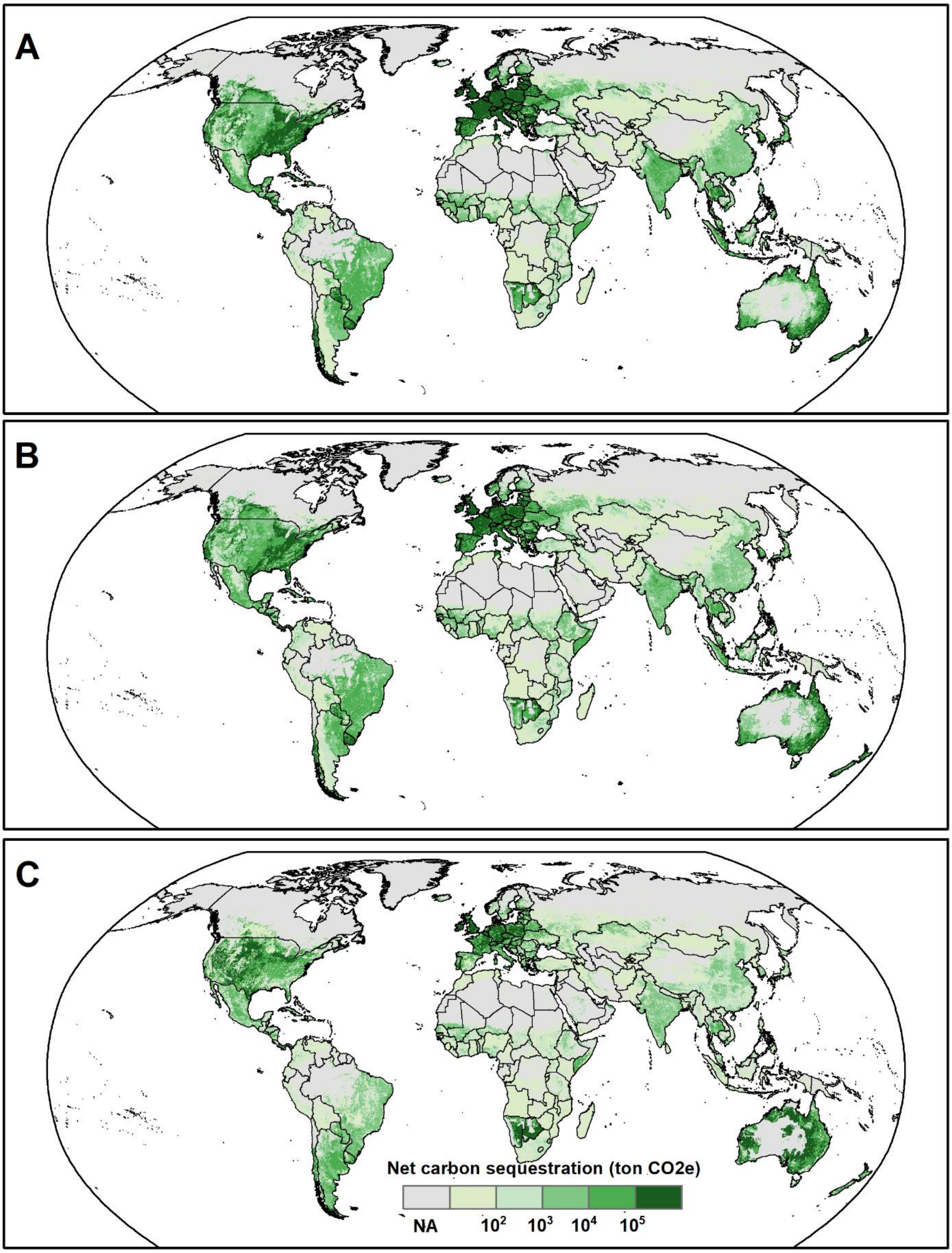
Supplementary Figure 7. Net carbon sequestration due to dietary shifts from national average diets to EAT diet in high-income countries for cropland (A) and pasture (B).



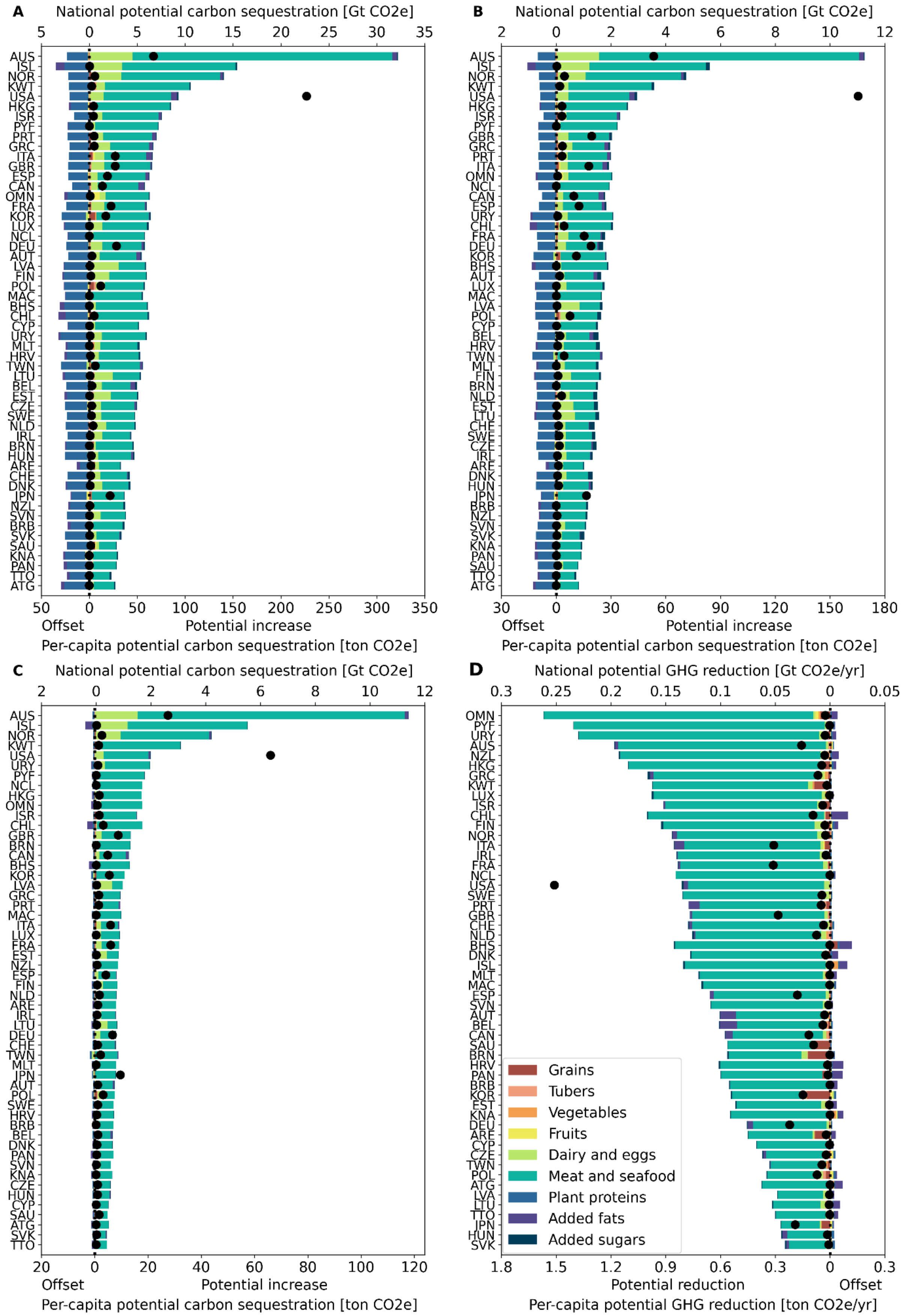
Supplementary Figure 8. Net carbon sequestration due to dietary shifts from national average diets to EAT diet in high-income countries. Increasing amount of carbon sequestration in spared land due to dietary change for AGBC (A), BGBC (B), SOC (C).



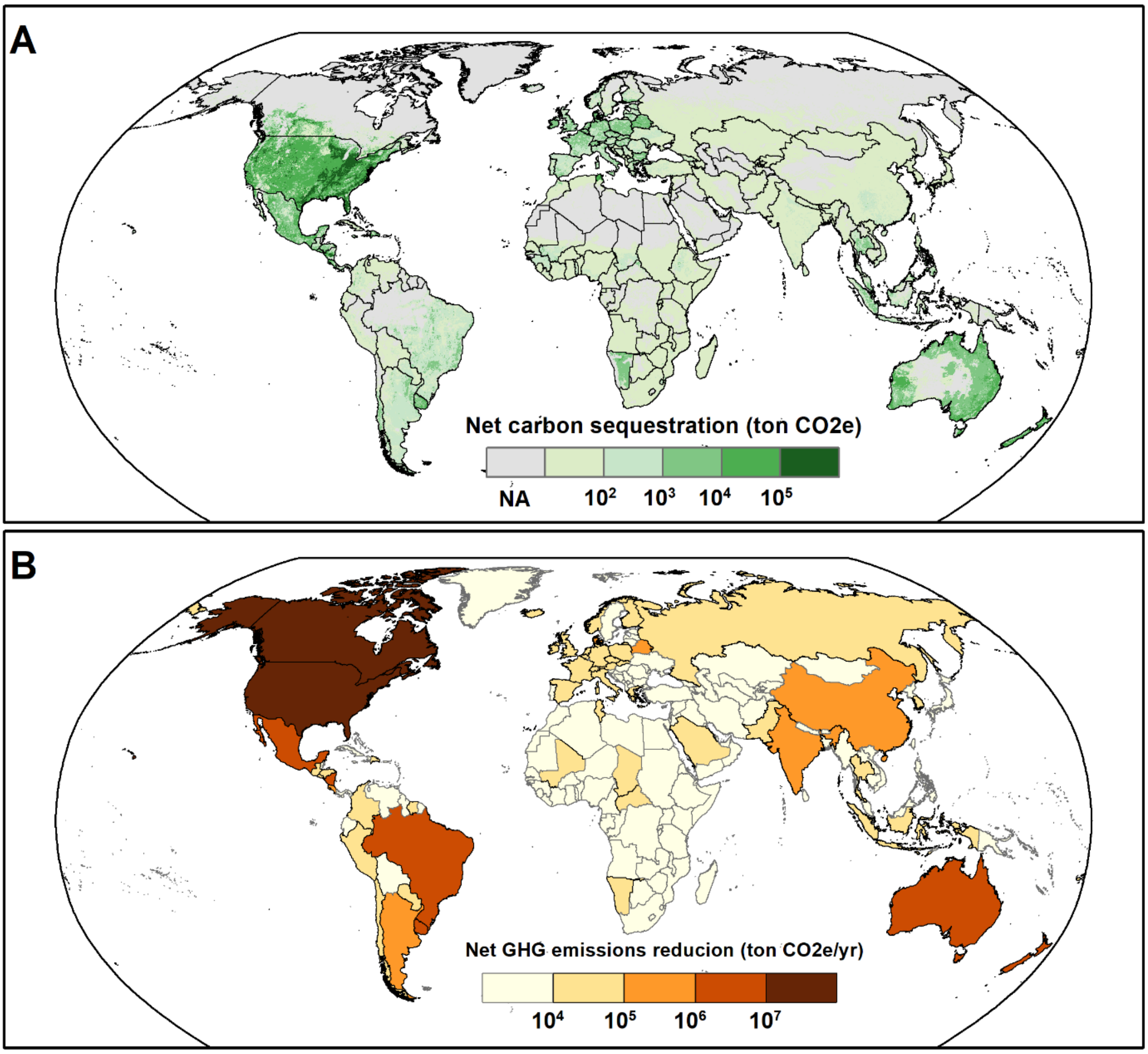
Supplementary Figure 9. Lower bound of net carbon sequestration due to dietary shifts from national average diets to EAT diet in high-income countries. Increasing amount of carbon sequestration in spared land due to dietary change for AGBC (A), BGBC (B), SOC (C).



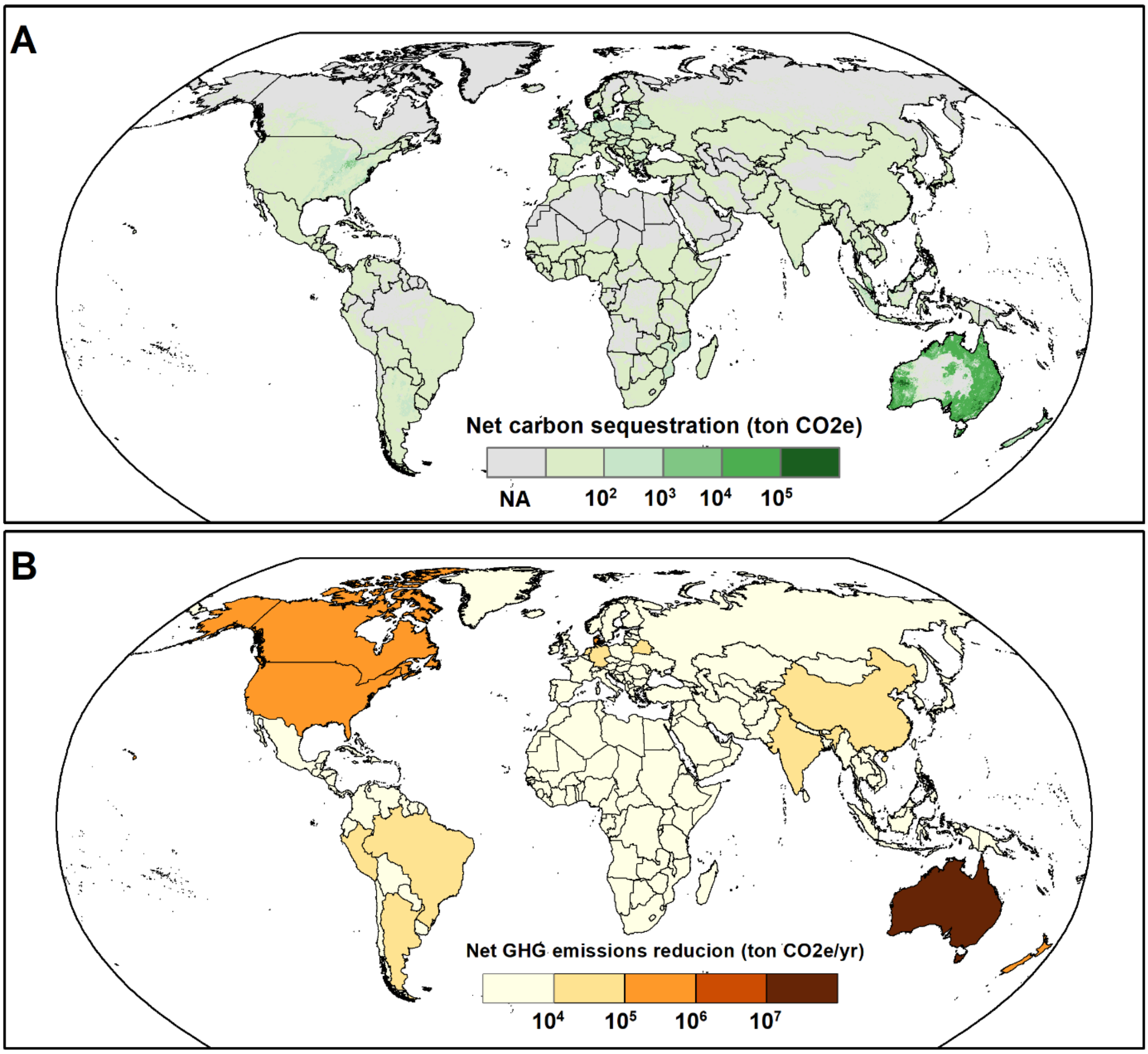
Supplementary Figure 10. Upper bound of net carbon sequestration due to dietary shifts from national average diets to EAT diet in high-income countries. Increasing amount of carbon sequestration in spared land due to dietary change for AGBC (A), BGBC (B), SOC (C).



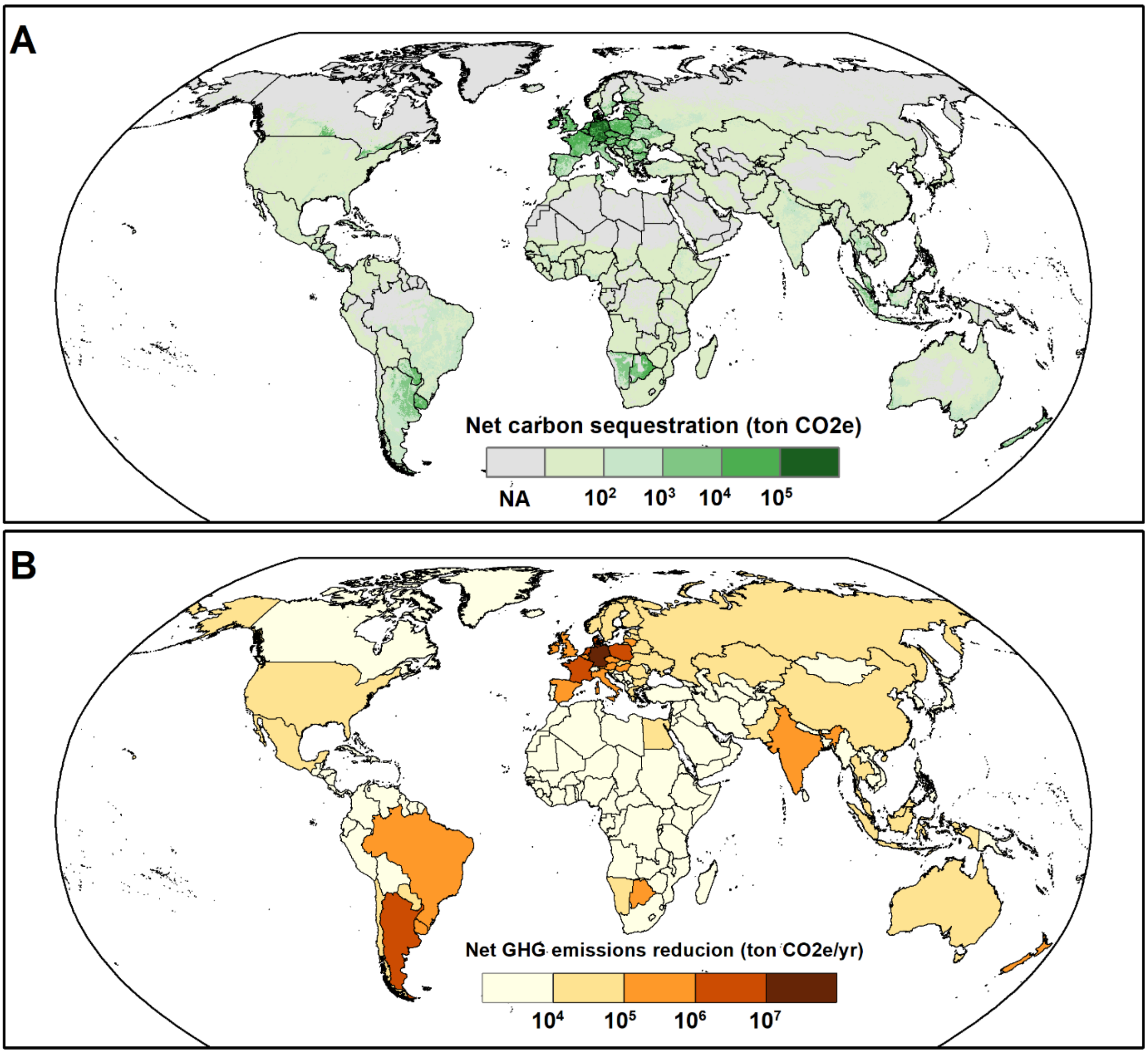
Supplementary Figure 11. National and Per-capita net carbon benefits due to dietary shifts from national average diets to EAT diet in individual high-income country by food category. Reductions/increases in carbon sequestration due to dietary change for AGBC (A), BGBC (B), SOC (C), and GHG reductions/increases (D) by food category. Bars give per-capita carbon sequestration and GHG emission changes by food categories, and dots give national net carbon sequestration and GHG emission changes. The potential increase of carbon sequestration is given by the carbon sequestration in potential natural vegetation minus that of current agricultural vegetation. The offset of carbon sequestration is given by the carbon sequestration in potential natural vegetation minus that of increased agricultural vegetation. The carbon reduction of GHG emission means the GHG reduction due to reduction of food categories, and the offset means the GHG increase due to increase of food categories.



Supplementary Figure 12. Changes in (A) net carbon sequestration (the sum of AGBC, BGBC, SOC), (B) net carbon emissions due to dietary change in the US (shown in Robinson projection).



Supplementary Figure 13. Changes in (A) net carbon sequestration (the sum of AGBC, BGBC, SOC), (B) net carbon emissions due to dietary change in the Australia (shown in Robinson projection).



Supplementary Figure 14. Changes in (A) net carbon sequestration (the sum of AGBC, BGBC, SOC), (B) net carbon emissions due to dietary change in Germany (shown in Robinson projection).

Supplementary Table 1 to Supplementary Table 11.

Supplementary Table 1. Crop-specific parameters used to calculate AGBC and BGBC

Supplementary Table 2. Mapping relationship between FABIO sectors and EAT diet groups

Supplementary Table 3. Food and energy composition of the EAT diet

Supplementary Table 4. Country Code and ISO3 for countries of FABIO

Supplementary Table 5. Mapping relationship of countries between FABIO and IFA

Supplementary Table 6. Mapping relationship of crops between FABIO and IFA

Supplementary Table 7. Mapping relationship of countries between FABIO and EXIOBASE

Supplementary Table 8. Mapping relationship of sectors between FABIO and EXIOBASE

Supplementary Table 9. Per-capita daily food difference between national average diet and EAT diet

Supplementary Table 10. Time horizon to potential natural vegetation (PNV) from current studies.

Supplementary Table 11 Percentage of carbon sequestration due to dietary change fulfilling national carbon dioxide removal (CDR) obligations in high-income countries.

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